Implementing Hager's exchange methods for matrix profile reduction.*

by

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Abstract

Hager recently introduced down and up exchange methods for reducing the profile of a sparse matrix with a symmetric sparsity pattern. The methods are particularly useful for refining orderings that have been obtained using a standard profile reduction algorithm, such as the Sloan method. The running times for the exchange algorithms reported by Hager suggested their cost could be prohibitive for practical applications. We examine how to implement the exchange algorithms efficiently. For a range real test problems, it is shown that the cost of running our new implementation does not add a prohibitive overhead to the cost of the original reordering.

Keywords: matrix profile, sparse matrices, exchange method.

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^{*} Current reports available from www.numerical.rl.ac.uk/reports/reports.html

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1 Introduction

If Gaussian elimination is applied to a symmetric positive-definite matrix A of order n, all zeros between the first entry of a row and the diagonal usually fill in (this happens if rows $2, 3, \ldots, n$ all have at least one entry to the left of the diagonal). Therefore, the total number of entries in each triangular factor is the sum of the lengths of the rows of the original matrix, where each length is counted from the first entry to the diagonal. This sum is also known as the **profile**.

A variety of methods have been proposed for choosing a permutation of the matrix that reduces the profile. Following the publication of the paper by Cuthill and McKee (1969), graph theory and level sets, in particular, became a standard approach for both bandwidth and profile reduction. proposed in the late 1970s and early 1980s include the Reverse Cuthill-McKee (George and Liu, 1981), the Gibbs-King (Gibbs, 1976) and the Gibbs-Poole-Stockmeyer (Gibbs, 1976, Lewis, 1982) algorithms. The Sloan algorithm (Sloan, 1986, 1989) offered a considerable improvement over these methods by introducing a second step in which the ordering obtained using the pseudo-diameter from a variant of the Gibbs-Poole-Stockmeyer algorithm was locally refined. The Sloan method has been widely used and a number of enhancements to the original algorithm have been proposed (see, for example, Duff, Reid and Scott, 1989, Kumfert and Pothen, 1997, and Reid and Scott, 1999). A high quality implementation of an enhanced version of the Sloan algorithm is available within the mathematical software library HSL (http://www.cse.clrc.ac.uk/Activity/HSL) as routine MC60.

A very different approach was described by Barnard, Pothen and Simon (1995). Their spectral method was based on computing the Fiedler vector of the Laplacian matrix associated with the matrix A. A similar idea was suggested independently by Paulino, Menezes, Gattass and Mukherjee (1994a, 1994b). Kumfert and Pothen (1997) proposed combining the second step of the Sloan algorithm with the spectral ordering. For large problems, the resulting hybrid algorithm has been shown to give significantly better orderings than either the spectral method or the Sloan method alone. The main disadvantage is that the hybrid algorithm requires the computation of the Fiedler vector of a large matrix, and this can add considerably to the reordering cost (Hu and Scott, 2001, report that the CPU time can be up to five times that for the Sloan algorithm).

Motivated by the success of multilevel algorithms for graph partitioning, Hu and Scott (2001) recently developed a **multilevel** algorithm for wavefront and profile reduction. A series of graphs is generated, each coarser than the preceding one. The enhanced Sloan algorithm is employed on the coarsest graph. The coarse graph ordering is then recursively prolonged to the next finer graph, with local refinement performed at each level. The final ordering on the finest graph gives an ordering for A. Extensive numerical experimentation has shown that the multilevel approach gives orderings of similar quality to that of the hybrid algorithm, whilst being significantly faster.

Hager (2000) suggested two methods for improving any given permutation

for profile reduction. His down exchange algorithm involves a cyclic permutation, that is, the successive exchange of rows (k, k+1), (k+1, k+2), ..., (l-1, l) of the permuted matrix and interchanging corresponding columns. For a given k, Hager finds the value of l that most reduces the profile. He performs a pass over the matrix with k taking the values n-1, n-2, ..., 1; he calculates l for each k and, if this gives a profile reduction, applies the corresponding permutation.

Hager's up exchange is similar, with the direction reversed. For a given k, he exchanges rows and columns $(k, k-1), (k-1, k-2), \ldots, (l+1, l)$, finding the value of l that most reduces the profile. He performs a pass over the matrix with k taking the values $2, 3, \ldots, n$.

Hager proposes using the down exchange and up exchange schemes in an iterative fashion: the down exchange algorithm is first applied, followed by the up exchange algorithm, followed by the down exchange algorithm, and so on.

In many applications, it is important that reordering the matrix to reduce the profile is done as quickly and efficiently as possible. If a large number of matrices having the same sparsity pattern are to be factored or if storage restrictions require the smallest possible profile, it may be worthwhile to spend a relatively large amount of time computing a permutation that minimizes the profile. However, if the matrix needs to be factored only once, the cost of reducing the profile must be compared with that required for the matrix factorization; in such circumstances, a slightly larger profile may be acceptable if it can be computed cheaply. Hager presents timings for his exchange algorithms that show they are expensive to run compared with algorithms such as the Sloan algorithm that are used to produce the initial reordering. Hager also reports that, in general, he found the down exchange algorithm to be significantly faster than the up exchange algorithm (typically by a factor of between 4 and 10). We have considered carefully how the exchange algorithms should be implemented. In Sections 2 and 3, we explain how to implement the down and up exchange methods efficiently. In particular, careful implementation of the up exchange algorithm results in it running much faster than Hager reported. Results for a set of test matrices arising from practical applications are presented in Section 4. The profile reductions achieved using the Hager exchanges are given together with the CPU times required to achieve these reductions. Concluding remarks are made in Section 5.

2 Implementation of the down exchange

Any reduction in the profile leads to a corresponding increase in the total number of zeros ahead of the first entries of the rows. Therefore, we can minimize the profile by maximizing this total. By symmetry, this is also the total number of zeros ahead of the first entries of the columns. This total is unaffected by column permutations, so we can delay applying them and work solely with row permutations in the body of the code. We need a representation of the pattern of the whole symmetric matrix, including the diagonal.

We have chosen to hold the structure of the original matrix unchanged while

the permutations are found. We hold the current permutation and its inverse in two integer arrays perm and inv_perm of length n and update these as each cyclic permutation (k,l) is found. This involves far less work than updating the matrix structure.

In describing the algorithm (and in writing the code) it is very important to distinguish between original row indices and permuted row indices. Unless otherwise stated, array subscripts and stored row indices refer to original indices so that they do not need to be altered with each cyclic permutation (k, l). In this description, 'first', 'second', 'in front', 'beyond', ... refers to the position in the column when the rows have been permuted. We hope that the context will make it clear whether the row index is original or permuted.

We define a gain to be a decrease to the profile and a loss to be an increase to the profile. The net gain is the difference between the gain and the loss resulting from a permutation. Thus, at each stage we are seeking the maximum net gain.

When permuted rows k and k+1 are exchanged, there is a gain of one for each column with its first entry in row k and its second entry after row k+1, and there is a loss of one for each column with its first entry in row k+1. As the further interchanges (k+1,k+2), ... are performed, there is a further gain in each column that gained from the first interchange until the second entry of the column is reached. There is also a loss of one as each other first entry is encountered. Hager sweeps forward from row k accumulating the net gain at each stage until there are no columns with a potential for gain. The row for which the maximum gain is found provides the index l.

We illustrate this by the example shown in Figure 1a. Exchanging rows 1 and 2 gives a gain in columns 1, 3, 4 and 6 and a loss in column 2. Following this with an exchange of rows 2 and 3 gives a further gain in columns 4 and 6 and a loss in column 5. Exchanging rows 3 and 4 gives a further gain in column 6 with no loss. No further gains are possible. The net gains are 3, 4, 5 so we choose l to be 4. The matrix pattern after the row exchanges is given in Figure 1b and Figure 1c shows the pattern after the row and column permutations.

	1	2	3	4	5	6
1	X		×	×		×
2		X				
3	X		X		X	
_	X			×	X	
5			×	×	X	×
6	×				×	×

Figure 1a. Original matrix.

```
3
1
^{2}
   ×
                        ×
              X
3
  \times
                   Χ
                       X
  X
              Χ
                  X
                            X
5
              \times \times
6
```

Figure 1b. Row permuted matrix

```
1
             3
                     5
                          6
                4
1
   X
2
        ×
                      ×
                 X
3
             X
                 \times \times
4
        X
            X
                 X
                          X
5
        X
          \times
                      X
                          X
6
                      X
```

Figure 1c. Row and column permuted matrix

An informal code to find l for a given k is as follows:

Note that the exit from the loop usually occurs quite early since the second entry of each column is usually near the first (it is often adjacent).

For efficient execution, it is clearly important to be able to find gain and loss quickly. We do this by using three integer arrays of length n:

- num_first(i) holds the number of columns with their first entry in row i, i = 1, 2, ..., n.
- num_second(i) holds the number of columns with their first entry in row k and second entry in permuted row i, i = 1, 2, ..., n.

• second(j) holds the permuted index of the second entry of column j if the first entry is in row k and zero otherwise, j = 1, 2, ..., n.

We can calculate num_second efficiently for each row k by starting with all components having the value zero and restoring this afterwards. We search each column j with a first entry in row k to find its second entry second(j) and add one to $num_second(second(j))$. Once l has been found, for each column j with a first entry in row k, we set $num_second(second(j))$ back to zero.

For each cyclic permutation (k, l), we also need to revise the array num_first. There is a change of first entry in a column only if its first entry is in row k and its second entry is not beyond row l. Therefore, for each column j with first entry in row k and $second(j) \leq l$, we subtract one from $num_first(inv_perm(k))$ and add one to $num_first(inv_perm(second(j)))$.

It is clear that we need to be able to find the columns with their first entry in row k quickly. We therefore link all the first entries that lie in a given row. We do this by using two further integer arrays of length n:

- start(i) holds the index of a column (if any) that has its first entry in row i, i = 1, 2, ..., n.
- next(j) holds the index of another column (if any) that has its first entry in the same row as column j, j = 1, 2, ..., n.

It is easy to update this for a cyclic permutation (k, l). We run through the column indices j in the linked list for row k; if $\mathtt{second}(j) \leq l$, we remove j from the list for row k and insert it at the front of the list for row $\mathtt{inv_perm}(\mathtt{second}(j))$. Inserting it at the front avoids the need to search the list.

3 Implementation of the up exchange

For the up exchange algorithm, we again maximize the total number of zeros ahead of the first entries of the columns. As before, we need a representation of the pattern of the whole symmetric matrix, including the diagonal, and work with row permutations only.

We again hold the structure of the original matrix unchanged while the permutations are found. We again hold the current permutation and its inverse in two integer arrays perm and inv_perm of length n and update these as each cyclic permutation (k, l) is found.

When rows k and k-1 are exchanged, there is a gain of one for each column with its first entry in row k-1 and a zero in row k, and there is a loss of one for each column with its first entry in row k. For efficient coding of the algorithm, we found it necessary to regard this as a gain of one for each column with its first entry in row k-1 and a loss of one for each column with an entry in row k and its first entry in row k or k-1 (so that a column with an entry in row k and it first entry in row k-1 contributes a net gain of zero).

In each further interchange, row k (temporarily in row m+1) moves to row m and row m moves to row m+1, m=k-2, k-3, ..., 1. There is a further

gain of one for each column with its first entry in row m and a further loss of one in each column with an entry in row k and its first entry in rows $k, \ldots m$.

We illustrate this by the example shown in Figure 2a with k=5. Exchanging row 5 with row 4 gives a gain in columns 4 and 6 and a loss in column 4. Following this with an exchange of row 5 (now in row 4) with row 3 gives a gain in column 3 and a loss in column 4. Next, the exchange of row 5 (now in row 3) with row 2 gives a gain in columns 2 and 5 and a loss in columns 2, 4 and 5. Finally, the exchange of row 5 (now in row 2) with row 1 gives a gain in column 1 and losses in columns 2, 4 and 5. The net gains are 1, 1, 0, -2, so we choose l=k-1=4. The matrix after the row permutation is given in Figure 2b and Figure 2c shows the matrix after the row and column permutations.

```
1
                      5
                          6
1
2
        X
3
            ×
4
                 X
                     Χ
                          X
5
        X
                 Χ
                     X
6
                 X
                          X
```

Figure 2a. Original matrix

	1	2	3	4	5	6
1	×					
2		X			X	
3			X			
4		X		X	X	
5				×	X	X
6				×		×

Figure 2b. Row permuted matrix

```
1
                         6
1
   X
2
        X
3
            X
4
        X
                 X
5
                     X
                         X
6
                     X
                         X
```

Figure 2c. Row and column permuted matrix

An informal code to find l for a given k is shown in Figure 3.

Figure 3.

To avoid unnecessary cycles of this loop, Hager holds the number of zeros in row k that have not already been used to reduce the profile, say in the variable nzk. The further improvement to the net gain is bounded by nzk-loss so the loop can be left if the inequality

```
net_gain + nzk - loss <= max_gain</pre>
```

holds. Unfortunately, nzk will start with a value near n, so that a large number of loop executions is likely to be needed.

Hager remarks that a row without any first entries can be skipped since it yields no gains and may yield losses; he uses a linked list to limit loop executions to rows with first entries. Since it is likely that there are many such rows, he also limits the length of each cyclic permutation to 1000.

The number of tests may be further reduced by taking advantage of the special role played by rows that have a first entry in a column that also has an entry in row k. We will call these **step** rows. Their significance lies in the fact that **loss** changes only in these rows. We store the permuted indices of these rows in the array **steps** and sort them in decreasing order. To find these indices quickly we need the integer array of length n:

• first(j) holds the index of the first entry of column j, j = 1, 2, ..., n.

To ensure that we include an interval with loss at its greatest (which is the number of entries in row k), we include 0 as a step row.

For efficient execution, it is important to be able to find gain quickly. We do this by using an array of size n:

• num_first(i) holds number of columns with first entry in row $i, i = 1, 2, \ldots, n$.

To avoid having to cycle though the loop of Figure 3, we also hold the accumulation of gain over rows that are adjacent in the permuted order. We do this by using another array of size n:

• gains(i) holds sum(num_first(inv_perm(i:n))), i = 1, 2, ..., n.

For each cyclic permutation (k, l), we need to revise these arrays. There is a change of first entry in a column only if it has an entry in row k and its first entry is not in front of row l. Therefore, for each column j with an entry in row k and $perm(first(j)) \geq l$, we add one to $num_first(inv_perm(k))$, subtract one from $num_first(first(j))$, and reset first(j). Only components $k, k-1, \ldots, l+1$ of gains change and these can be recalculated in the loop that resets the changed components of the permutation and inverse permutation vectors.

The loss value is fixed for each interval between step rows, that is, for m in the range

$$p = steps(i) + 1 > m > q = steps(i+1) + 1$$

and the net gain is

$$\mathtt{net_gain}(m) = \mathtt{net_gain}(p) + \mathtt{gains}(m) - \mathtt{gains}(p) - \mathtt{loss} * (p-m).$$

The inequality

$$net_gain(m) \le net_gain(p) + gains(q) - gains(p) - loss*(p-m).$$

may be deduced. If m is to be advantageous, the inequality

$$net_gain(m) > max_gain$$

must hold, where max_gain is the best net gain found up to and including row p. A fortiori, the inequality

$$net_gain(p) + gains(q) - gains(p) - loss*(p-m) > max_gain$$

must hold, that is, the inequality

$$m > p - (\text{net_gain}(p) + \text{gains}(q) - \text{gains}(p) - \text{max_gain})/\text{loss}$$

must hold. This inequality may tell us immediately that there is no advantageous row in the interval. Otherwise, it gives us a new bound

$$q' = \mathtt{int}(p + (\mathtt{net_gain}(p) + \mathtt{gains}(q) - \mathtt{gains}(p) - \mathtt{max_gain}) / \mathtt{loss})$$

beyond which we do not need to test. If q' > q, we apply the same test with q' replacing q; otherwise, we test the remaining interval directly.

Our code has an outer loop which we call outer within which we test a single interval thus:

```
p = steps(i-1) + 1
   q = steps(i) + 1
! Search between p-1 and q
      next = p - (net_gain+gains(q)-gains(p)-max_gain)/loss
      if (next >= p) exit outer
      if (next <= q) exit
      q = next
   end do
! Simple search between p-1 and q
   do p = p-1,q,-1
      net_gain = net_gain + num_first(inv_perm(p)) - loss
      if (net_gain > max_gain) then
        1 = p
        max_gain = net_gain
      end if
      if (net_gain+gains(q)-gains(p)-loss <= max_gain) exit</pre>
  end do
```

Figure 4.

We treat the rows in which loss is zero specially (they are always advantageous) and apply this algorithm to each interval in turn. The effect of using this code was dramatic; this is illustrated in Section 4.

4 Numerical experiments

In this Section we present numerical results. Our test problems are listed in Table 4.1. This set is taken from Kumfert and Pothen (1997) and represents a range of application areas: structural analysis, fluid dynamics, and linear programs from stochastic optimization and multicommodity flows. All our experiments were performed on a Compaq DS20, using the Compaq Fortran 90 compiler V5.4A-1472 with the -O option. The statistic used in our tables of results is the **normalised profile** defined by

$$\frac{P}{n}$$

where n is the order of the matrix and P the profile. All CPU times are given in seconds.

In Table 4.2, we present the normalised profiles for the original matrix, for the enhanced Sloan algorithm as implemented in the HSL code MC60, for the hybrid algorithm (Kumfert and Pothen, 1997) and for the multilevel algorithm (Hu and Scott, 2001). For each ordering we also give the normalised profiles after applying the down exchange algorithm followed by the up exchange algorithm five times. We see that the largest reductions in the profile result from the initial reordering; using the Hager exchange algorithms results in further more modest reductions. The size of these reductions is very problem

Identifier	Order	Entries	$\operatorname{Comment}$
barth	6691	19748	2D CFD problem
barth4	6019	17473	2D CFD problem
barth5	15606	45878	2D CFD problem
bcsstk30	28924	1007284	3D stiffness matrix
commanche_dual	7920	11880	3D CFD problem
copter1	17222	96921	3D structural problem
copter2	55476	352238	3D structural problem
finance256	37376	130560	Linear program problem
finance512	74752	261120	Linear program problem
ford1	18728	41424	3D structural problem
ford2	100196	222246	3D structural problem
nasasrb	54870	1311227	3D structural problem
onera_dual	85567	166817	3D CFD problem
pds10	16558	66550	Linear program problem
shuttle_eddy	10429	46585	3D structural problem
skirt	45361	1268164	3D structural problem
tandem_dual	94069	183212	3D CFD problem
tandem_vtx	18454	117448	3D CFD problem

Table 4.1: The test suite

dependent. For a number of problems, including bcsstk30, shuttle_eddy, and skirt, the improvements are less than 1 per cent. However, the reductions can be more significant. For example, for ford1 and ford2, the MC60 profiles are improved by 21 and 18 per cent, respectively. We remark that it is important to have a good initial reordering before the application of Hager's exchange algorithms. For our test cases, the smallest profiles were obtained after applying Hager's algorithm to the best initial reordering.

In Table 4.3, we present the normalised profiles and CPU times for applying the exchange algorithms to the MC60 orderings. Results are given for a single application of Hager down/up, for repeating the down/up exchanges 5 times, and for repeating the down/up exchanges without limit until there is no further reduction in the profile. The greatest reductions result from the first application of the exchange algorithm, although for a number of problems, including ford2 and tandem_dual, useful further reductions are achieved by repeatedly applying the exchange algorithm. On the basis of these results, by default we limit the number of down/up exchanges to 5. For a number of problems, the cost of a single application of the exchange algorithms is significantly greater than the initial MC60 ordering cost but, because of our efficient implementation of the Hager up exchanges, we feel that most users would be unlikely to find this cost prohibitive.

Our final implementation of the up exchange algorithm has had a huge effect on the CPU time, and we illustrate this in Table 4.4. We denote by Simple the

Table 4.2: Normalised profiles for the original matrix, the MC60, hybrid and multilevel orderings, and for these orderings followed by 5 applications of the Hager down/up exchanges (denoted by +Hager).

Identifier	Original	MC60		Hybrid		Multi.	
			$+ \mathrm{Hager}$		$+ { m Hager}$		$+ \mathrm{Hager}$
barth	2370.6	70.8	67.7	59.3	56.8	62.1	59.6
barth4	359.7	54.5	51.2	47.9	45.3	49.3	46.6
barth5	261.0	91.8	84.9	82.5	77.6	92.7	81.3
bcsstk30	543.4	543.4	534.2	272.5	272.1	273.6	273.0
$commanche_dual$	2089.8	42.3	39.3	43.8	41.9	35.1	33.3
copter1	1103.3	346.2	331.3	354.7	331.5	351.6	335.5
copter2	19541.8	685.2	650.9	590.7	562.9	698.1	654.5
finance256	6459.7	169.4	167.4	172.3	168.7	127.4	124.4
finance512	12859.2	158.2	156.9	156.8	152.1	114.0	113.2
ford1	1880.4	126.3	99.9	104.3	88.8	101.9	85.2
ford2	3715.6	407.9	334.2	358.6	299.0	304.8	260.0
nasasrb	371.2	346.9	344.3	351.7	347.1	323.1	321.2
$onera_dual$	8287.8	1025.2	933.7	545.1	520.9	656.0	628.8
pds10	1090.3	559.0	535.0	532.0	513.5	632.3	559.8
$\mathtt{shuttle_eddy}$	1118.7	59.4	59.2	57.0	57.0	57.2	57.0
skirt	1011.1	808.0	807.9	615.7	615.6	657.7	657.2
$tandem_dual$	5183.0	701.3	626.2	448.5	432.7	420.6	407.9
$tandem_vtx$	4390.7	329.1	309.8	282.6	271.8	276.4	268.4

Table 4.3: Normalised profiles and CPU times for MC60 and for applying the Hager exchange algorithm to the MC60 orderings. The numbers in parentheses are the number of times the down/up exchange algorithms are applied; inf. indicates no limit.

Identifier	MC60		+Hager		+Hager		+Hager		
			down/1	down/up(1)		down/up(5)		down/up (inf.)	
	$\mathbf{Profile}$	$_{ m Time}$	$\mathbf{Profile}$	$_{ m Time}$	$\mathbf{Profile}$	$_{ m Time}$	$\mathbf{Profile}$	Time	
barth	70.8	0.05	68.1	0.02	67.7	0.09	67.6	0.16	
barth4	54.5	0.03	51.3	0.02	51.2	0.07	50.8	0.32	
barth5	91.8	0.10	85.4	0.08	84.9	0.22	82.7	0.94	
bcsstk30	543.3	0.96	534.2	0.41	534.2	1.23	534.2	1.23	
${\tt commanche_dual}$	42.3.2	0.03	39.6	0.02	39.3	0.09	39.1	0.18	
copter1	346.2	0.13	331.3	0.20	331.3	0.31	331.3	0.31	
copter2	685.2	0.60	653.7	0.70	650.9	1.88	650.0	7.72	
finance256	169.4	0.26	167.4	0.10	167.4	0.38	167.4	0.38	
finance512	158.2	0.55	156.9	0.22	156.9	0.81	156.0	0.82	
ford1	126.3	0.09	105.5	0.14	99.9	0.36	97.5	1.41	
ford2	407.9	0.71	349.3	2.71	334.2	5.14	328.9	15.31	
nasasrb	346.0	1.29	344.3	0.55	344.3	2.80	344.3	2.80	
onera_dual	1025.2	0.65	955.0	3.39	933.7	6.62	910.0	28.13	
pds10	559.0	0.13	536.6	0.10	535.5	0.35	535.0	0.48	
$shuttle_eddy$	59.4	0.06	59.2	0.02	59.2	0.11	59.2	0.37	
skirt	808.0	1.28	807.8	0.56	807.9	1.69	807.9	1.69	
$tandem_dual$	701.3	0.66	650.1	2.11	626.2	4.90	611.0	17.34	
$tandem_vtx$	329.1	0.15	315.7	0.11	309.8	0.44	305.5	2.29	

implementation based on the Figure 3 code; Simple (1000) denotes combining this with Hager's proposed limit of 1000 on the length of each cylic permutation; New denotes our final implementation that uses the Figure 4 code. In each case, the Hager down exchange followed by the up exchange is applied 5 times to the ordering obtained from MC60. For comparison, timings are also given for MC60.

Table 4.4: CPU times for MC60 and for 5 applications of the Hager down/up exchanges. Simple is based on the Figure 3 code; Simple(1000) use the Figure 3 code with a limit of 1000 on the length of each cylic permutation; New uses the Figure 4 code.

Identifier	MC60	Simple	Simple(1000)	New
barth	0.05	0.78	0.71	0.09
barth4	0.03	0.57	0.55	0.07
barth5	0.10	4.32	1.82	0.22
bcsstk30	0.96	2.11	3.33	0.09
$commanche_dual$	0.03	1.52	0.81	0.09
copter1	0.13	3.24	1.53	0.31
copter2	0.60	40.31	7.86	1.88
finance256	0.26	19.26	3.27	0.38
finance512	0.55	78.64	6.73	0.81
ford1	0.09	7.38	2.13	0.36
ford2	0.71	256.07	15.04	5.14
nasasrb	1.29	10.33	7.46	2.80
onera_dual	0.65	237.05	15.98	6.62
pds10	0.13	6.12	2.12	0.35
${ t shuttle_eddy}$	0.06	1.23	1.03	0.11
skirt	1.28	4.97	3.71	1.69
$tandem_dual$	0.66	247.55	14.78	4.90
$tandem_vtx$	0.15	3.68	2.16	0.44

We observe that, for the larger problems, Simple(1000) is much faster than Simple. The savings for problems ford2, nasasrb and tandem_dual are particularly impressive. However, limiting the length of the cylic permutation does not necessarily result in a reduction in the CPU time when the Hager down/up exchanges are applied more than once; this is illustrated by problem bcsstk30. Furthermore, we found that it may result in a slight loss of quality. For example, for problem ford2, Simple reduces the MC60 profile by 18 per cent whereas the reduction with Simple(1000) is 16 per cent. Simple and New produce the same profiles but the performance of New is a dramatic improvement over that of Simple. We did experiment with limiting the length of the cylic permutation within New but decided against incorporating such a limit because of the possibility of larger profiles and, with the efficiency of New, the CPU time savings were small.

Table 4.5 presents results for three problems in greater detail. For each application of an exchange algorithm we record the CPU time taken together with the total reduction in the normalised profile achieved so far. The problems

Table 4.5: The reductions in the normalised MC60 profiles and the CPU times taken for the Hager down and up exchange algorithms.

Iteration		commanche	_dual	ford2		pds10)
		Total		Total		Total	
		Reduction	$_{ m Time}$	Reduction	Time	Reduction	Time
1	down	2.593	0.013	37.272	1.357	22.064	0.060
	up	2.682	0.011	58.606	1.444	22.326	0.041
2	down	2.820	0.006	63.464	0.472	23.761	0.025
	up	2.846	0.010	65.226	0.327	23.842	0.040
3	down	2.962	0.006	67.794	0.302	23.906	0.024
	up	2.978	0.011	69.377	0.316	23.908	0.040
4	down	3.046	0.005	70.981	0.285	23.910	0.023
	up	3.050	0.011	71.866	0.269	23.910	0.040
5	down	3.060	0.006	72.900	0.231	23.910	0.023
	up	3.065	0.011	73.679	0.262	23.910	0.040
6	down	3.072	0.005	74.513	0.229	23.910	0.023
	up	3.074	0.011	75.136	0.227	23.911	0.040
7	down	3.131	0.006	75.739	0.251	23.911	0.023
	up	3.141	0.011	76.182	0.233	23.911	0.037
8	down	3.147	0.005	76.669	0.198		
	up	3.147	0.011	76.958	0.231		
9	down	3.155	0.005	77.366	0.206		
	up	3.156	0.011	77.629	0.225		
10	down	3.160	0.006	77.785	0.193		
	up	3.160	0.011	78.047	0.238		
11	down	3.160	0.005	78.219	0.186		
	up	3.160	0.011	78.295	0.213		
12	down			78.330	0.183		
	up			78.496	0.211		
13	down			78.591	0.183		
	up			78.609	0.208		
14	down			78.640	0.183		
	up			78.672	0.212		
15	down			78.724	0.188		
	up			78.737	0.211		
20	down			78.869	0.180		
	up			78.883	0.220		
25	down			78.884	0.178		
	up			78.885	0.207		
30	down			78.912	0.180		
	up			78.912	0.207		

were chosen to illustrate the different behaviours we observed. In each case, the first application of the down exchange gave the largest profile reduction. For pds10, applying the up exchange gave a further improvement of less than 2 per cent of the first reduction and stagnation was quickly reached. For commanche_dual, the first up exchange gave a 3 per cent reduction and most of the reduction resulting from repeated applications of the Hager algorithms came from the down exchanges. The first up exchange for ford2 gave a reduction of about 37 per cent. Thereafter the improvements rapidly declined to less than 1 per cent but a total of 30 iterations were required until there was no improvement at all. Regarding CPU times, after the first down/up exchange, the CPU times for each exchange quickly become constant, with each up exchange generally taking less than twice as long as the corresponding down exchange.

5 Concluding remarks

We have examined in detail how to efficiently implement the exchange algorithms of Hager. In particular, we have described how to implement the up exchanges so that their cost is no longer prohibitive. Our implementations have turned what are interesting profile reduction algorithms into practical algorithms that can be used to refine existing orderings. Based on our findings, we plan to include our codes in HSL as routine MC67. MC67 will allow the user to apply the Hager down/up exchanges to any given ordering; in particular, the user interface will be designed so that it will be straightforward for the user to run the exchange algorithms to refine the ordering produced by the HSL code MC60. The limit on the number of iterations will be a parameter under the user's control.

6 Acknowledgements

The second author was funded by the EPSRC Grant GR/M78502.

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